Prognostics and Diagnostics of Rotorcraft Bearings

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ABSTRACT

This paper presents a diagnostic and prognostic approach for rotorcraft bearing health monitoring using the Hilbert-Huang Transform (HHT). The HHT transforms a raw vibration data into in a two-dimensional time-frequency domain by extracting instantaneous frequency components within the signal through an empirical mode decomposition EMD process. EMD transforms the complex vibration signal into simple oscillatory modes called intrinsic mode functions (IMFs). Since the IMFs are obtained based on the local characteristic time scale of the data, they can be used to analyze the nonlinear and nonstationary bearing degradation processes. In performing diagnostic decisions, the work presented here uses the energy ratios of the highest two intrinsic modes and the respective marginal frequencies as condition indicative features. The approach has been tested using experimental data obtained from seeded spall and corrosion tests on AH-64 Apache hanger bearings.

INTRODUCTION

As a critical component in the rotorcraft system, effective health monitoring of bearings has attracted increasing attention from the research community. Early detection of bearing degradation allows the maintainer to plan corrective actions so as to minimize the impact to readiness, and in many cases to minimize collateral damage. Of the various bearing health monitoring techniques, such as oily debris analysis, acoustic emission, etc, vibration measurement remains to a reliable and cost effective technique [1,2].

Traditional vibration-based diagnostics rely on frequency domain analysis such as the fast Fourier Transform (or FFT). In the frequency domain, the vibration amplitude at the characteristic defect frequencies, also known as bearing fault frequencies (BFFs), are used to make diagnostic inference about bearing conditions [2,3]. A condition monitor that relies only on BFFs, however, doesn't always perform well because: (i) in many cases, particularly at the early stage of failure, the raw vibration signal has a very low signal to noise ratio (SNR) resulting in the fault frequencies being buried under the noise floor, (ii) in the case of wide spread defects such as corrosion, the fault frequency do not generally occur at a single repeatable frequency and hence no clear BFF can be established.

Bearing condition monitoring using linear and stationary signal processing techniques such as the ubiquitous Fourier transform or power spectrum analysis

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have been widely implemented [1-3]. Stationary vibration is one in which its properties such as frequency content, energy distribution are time-invariant. Bearing damage progression, however, is a localized and transient event in which the frequency content of the signal evolves with time. The transient nature of the signal makes the underlying assumption of stationarity as required by the Fourier transform invalid. Hence nonstationary signal processing techniques are required.

The earliest nonstationary signal processing technique was the short-time Fourier transform (STFT), which divides a time series x(t) into a series of small overlapping windowed pieces. The Fourier transforms of these small pieces is then assembled to obtain the time-frequency response of the signal as [4]:

$$F_{\mathrm{STFT}}(t,\omega)=\frac{1}{2\pi}\int_{-\infty}^{+\infty}x(t)h(t-\tau)e^{-j\omega t}dt \tag{1}$$

here h(t) is a window function such as Hann window or Gaussian hill, ω is angular frequency. The STFT is most useful when the physical process is linear, so that the superposition of sinusoidal solution is valid and time is locally stationary or when the Fourier coefficients are varying slowly. The main limitation of the STFT is that it uses the same window size to analyze the entire time series. A constant window size that matches the specific frequency content of an evolving signal cannot be known a priori [6].

Wavelet transform (WT) seeks to address the drawbacks of the STFT by implementing a windowing technique with variable sized regions. WT decomposes a time series into local time-dilated and time-translated wavelet components using time-frequency atoms or wavelets ψ as [7]:

$$\mathrm{F}_{\mathrm{WT}}(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{2}$$

where ψ(·) is the basic wavelet function, a is the scale and b is the time shift. Wavelet analysis is attractive because it has uniform temporal resolution for all frequency scales and as such it can characterize gradual changes in frequency. The limitation of WT, however, is that it uses the same wavelet function to analyze an entire data which unfortunately leads to a subjective assumption on the characteristic of the analyzed signal. As a consequence, only signal features that correlate well with the shape of the basic wavelet function have a chance to lead to coefficients of high value and all other features will be masked or completely ignored.

The FFT, STFT, and WT, techniques are based on linear and stationary assumption, linear and locally-stationary assumption, and linear and nonstationary assumption respectively. Unfortunately vibration data from a degrading bearing can only be accurately represented as a nonlinear and nonstationary process making these techniques invalid.

A recently developed method, known as the Hilbert-Huang transform (HHT) [9] establishes a viable signal processing approach to represent nonlinear and nonstationary vibration signals as presented in the next section.

THE HILBERT-HUANG TRANSFORM (HHT)

The HHT represents a vibration signal in time-frequency domain by combining the empirical mode decomposition (EMD) with the Hilbert transform (HT). The Hilbert transform (HT) is a convolution of a signal x(t) with a function $h(t)=1/\pi t$ and it consists of passing a signal through a system which leaves the magnitude unchanged, but changes the phase of all frequency components by π/2. The HT of a signal x(t) is given by [6,9]:

$$F_{HT}\{x(t)\}=y(t)=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(t)}{t-\tau}dt \tag{3}$$

The analytic signal denoted z(t) is constructed by adding the original signal x(t) to its Hilbert transform y(t) as $z(t)=x(t)+jy(t)$ and in polar coordinates $z(t)=a(t)\exp(j\theta(t))$. Where,

$$\begin{cases} a(t)=\sqrt{x^2(t)+y^2(t)} \\ \theta(t)=\tan^{-1}\left(\frac{y(t)}{x(t)}\right) \end{cases} \tag{4}$$

here a(t) and θ(t) are the instantaneous amplitude and the instantaneous phase angles of the analytic signal z(t). The instantaneous frequency is given by the time derivative of the phase angle θ(t) as [9,10]:

$$\omega(t)=\frac{d\theta(t)}{dt}=\frac{\dot{y}(t)x(t)-y(t)\dot{x}(t)}{x^2(t)+y^2(t)} \tag{5}$$

To ensure that the instantaneous frequency obtained from the derivative operations in (5) is physically meaningful, the instantaneous phase must be single valued function (or a mono-component signal). For multiple frequency component signals, such as the vibration signal from bearings, EMD has to be performed on the signal. The EMD technique iteratively decomposes a signal into a number of simple oscillatory modes called intrinsic mode functions (IMFs). To extract the IMF's from the vibration signal a sequential *sifting* process is conducted [9]. In the first step of EMD, one identifies all the local maxima and minima of the signal and then generates the upper and lower envelop functions. If the mean of the upper and lower envelops is $m_1(t)$, then the first IMF $h_1(t)$ is defined by:

$$x(t)-m_1(t)=h_1(t) \tag{6}$$

By definition $h_1(t)$ is an IMF if the following two conditions are satisfied [9]: (i) the number of extrema and the number of zero crossings are either equal or differ by at most one, (ii) at any point, the mean value between the envelop defined by the local minima is zero. If $h_1(t)$ does not satisfy the above two requirements, the sifting process is repeated sequentially for as many steps as it is needed to reduce the signal to an IMF. In the subsequent sifting step, $h_1(t)$ is treated as the original data, and then $h_1(t)-m_{11}(t)=h_{11}(t)$, where $m_{11}(t)$ is the mean of the upper and lower envelops of $h_1(t)$. In general the sifting process is repeated up to k times. Throughout the iteration process the difference between the signal and the mean envelop values, $h_{1k}(t)$, is calculated by:

$$h_{1(k-1)}(t) - m_{1k}(t) = h_{1k}(t) \tag{7}$$

where $m_{1k}(t)$ is the mean envelop value after the k^{th} iteration, and $h_{1(k-1)}(t)$ is the difference between the signal and the mean envelop values at the $(k-1)^{th}$ iteration. The function $h_{1k}(t)$ is then defined as the first IMF component and denoted by:

$$c_1(t) = h_{1k}(t) \tag{8}$$

After separating $c_1(t)$ from the original signal $x(t)$, the residue is obtained as:

$$r_1(t) = x(t) - c_1(t) \tag{9}$$

Subsequently, the residue $r_1(t)$ is taken as if it were the original data and the above iteration process is repeated to extract the rest of the IMFs inherent in the signal $x(t)$ as, $r_2(t) = r_1(t) - c_2(t), \cdots, r_n(t) = r_{n-1}(t) - c_n(t)$. The sifting process is terminated when the residue $r_n(t)$ becomes a monotonic function from which no further IMFs can be extracted [9]. The original signal $x(t)$ can be reconstructed from its IMFs as [6]:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{10}$$

Having obtained the IMFs using the EMD process, the Hilbert transform is applied to each IMF component as:

$$\mathrm{HT}\left[c_i(t)\right] = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{c_i(t)}{t-\tau} d\tau \tag{11}$$

The analytic signal is defined as, $z_i(t) = c_i(t) + j\mathrm{HT}\left[c_i(t)\right]$ and in polar coordinates $z_i(t) = a_i(t) e^{j\omega_i(t)}$. The instantaneous amplitude and phase angles are calculated using equations (4) and (5) with $c_i(t)$ and $H[c_i(t)]$ replacing $x(t)$ and $y(t)$ respectively. The original vibration signal can be reconstructed by assembling the instantaneous frequencies and instantaneous amplitudes as:

$$x(t) = \mathrm{Re} \sum_{i=1}^{n} a_i \exp\left(j \int \omega_i(t) dt \right), \tag{12}$$

The term $r_n(t)$ is not included in equation (12) as it is a monotonic function with no contribution to the frequency content of the signal. Equation (12) is designated as the Hilbert-Huang spectrum $H(\omega, t)$ and it allows three-dimensional visualization of the data in which amplitude is plotted as the height in the time-frequency plane.

FEATURE EXTRACTION

To perform diagnosis, one needs to select and extract features from the vibration signal that reveal the fault signatures and trend with fault severity. In the time domain, available features are root-mean-square (RMS), kurtosis, crest factor, impulse factor, shape factor, and clearance factor of the vibration signal [2]. Some of these features are good indicators for incipient localized or discrete damages such as spalling however, they are not effective in detecting wide spread failure such as corrosion. Even for spalling, when the defect becomes severe and spreads across the bearing surface, the vibration signal becomes more random and the statistical signature becomes buried again resulting in the drop to seemingly normal level of time domain features.

In the work presented here two different features are extracted. The first feature is the maximum amplitude frequency of the intrinsic mode functions (IMFs) of the highest and the second highest mode functions. This feature is obtained by taking the fast Fourier transform (FFT) of the two top IMFs. The second feature is the energy ratio of the first two highest IMFs. To obtain the second feature, the signal energy of the IMFs is calculated and divided by the total energy of the signal. The linear projection of these two features known as principal component (PCA) is then used as condition indicative parameter. Experimental data from spalled and corroded AH-64 bearings is used to validate the HHT based analysis technique and the feature vectors extracted here.

EXPERIMENTAL DATA

In order to obtain vibration data well correlate to the damage severity levels of the test bearings, a seeded fault test is conducted on a series of nominally identical AH-64 hanger bearings [11]. The latter is a single row, double sealed grease packed ball bearing lubricated with grease that conforms to MIL specification. The test was run on a component level test rig consisting of variable speed electric motor adapted to test similar classes of bearings. Table 1 shows specimen specifications and the severity of the seeded fault introduced in the specimens.

TABLE 1. BEARING TEST SPECIMENS

Bearing	Damage type Trench (width x depth)	Damage Severity
001BL	Baseline	Healthy
001BLr*	Baseline	Healthy
025LT	0.011" x 0.007" trench	Light
026MT	0.029" x 0.015" trench	Moderate
027ST	0.045" x 0.023" trench	Severe
019SC	Corrosion	Severe^{+}
020SC	Corrosion	Severe^{+}
021SC	Corrosion	Severe^{+}

*Baseline repeat test. $^{+}$By visual inspection.

Vibration data is collected from accelerometer installed on the housing of the bearing. Two different types of faults are seeded in the bearings. First, three different sizes of semi-circular trenches are cut in the inner race of three bearings. Second, corrosion is introduced in another set of three bearing by forcing salt water in the grease and storing the bearings until the corrosion reaches certain level deemed severe by visual inspection. In all cases the same radial load is applied and the test shaft-speed is maintained identical. Vibration data is collected at sampling rate of 120 kHz for five seconds at 15min intervals. Detail experimental setup, test procedure and photos of the test rig and test samples are given on the work of Dykas et.al [11].

Figure 1a (top) shows plots of the raw sensor data from a bearing with a severe trench (specimen 027ST) and a corroded bearing (specimen 021SC). The fast Fourier transforms showing the frequency spectrum of the two test bearings are shown in Figure 1b. Clearly, the very large seeded trench of 027ST has resulted in large signal to noise ratio as indicated by the easily identifiable periodic pulse on the raw time series. Moreover, the fundamental ball-pass fault frequencies are clearly shown on the spectrum plot of the data. The raw sensor data of the corroded bearing, however, shows a less identifiable pulse and the fault frequencies didn't occur at repeatable frequencies. Corrosion causes vibration to have a higher energy and there appears to be some spectral smearing in the frequency.

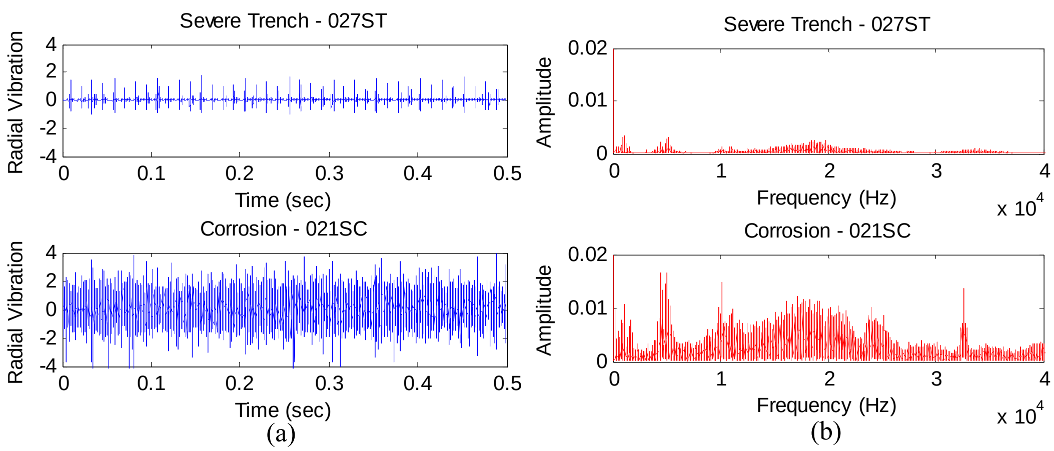


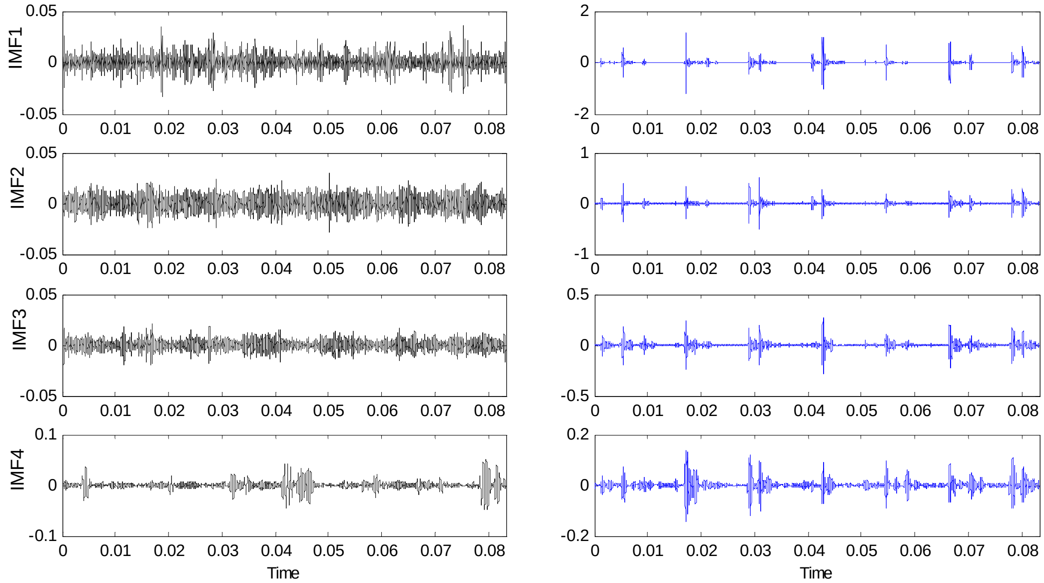
Figure 1. Raw vibration signals of spalled and corroded bearings: (a) Time, and (b) Frequency domains.

ANALYSIS RESULTS

The ability of the nonlinear and nonstationary Hilbert-Huang transform for diagnosing bearing defects was first studied on bearings with seeded trenches (specimens 025LT, 026MT, and 027ST). Shown in Figure 2 is a comparison of the extracted IMF's between signals from healthy *Baseline* and defective bearings. The corresponding HHT analyses are illustrated in Figure 3. For the defective bearing, the transient vibration caused by the defects are shown throughout the spectrum particularly in the frequency range of 1-3 kHz range. In addition these transients have shown a repetitive pattern that corresponds to the BPFO (ball passing outer) frequency of the bearing. The healthy bearing, in comparison showed no high frequency components or repetitive signal patterns since no defect is present.

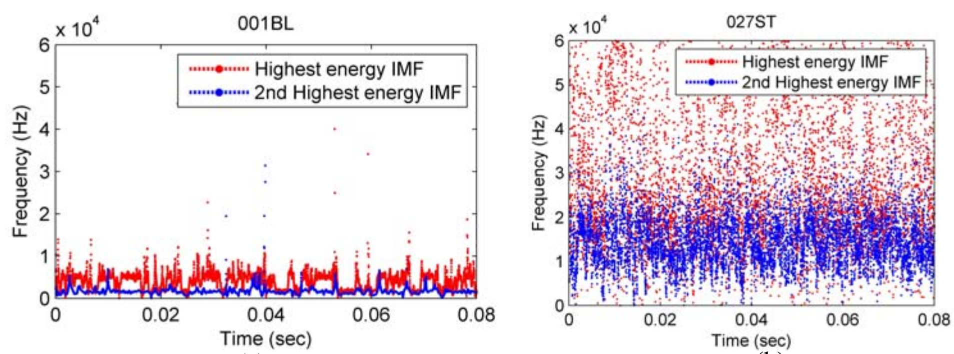
Figure 4 shows scatter plots of the condition indicative features for both the spalled and corroded bearings. As can be seen, the level means of the spalled bearing is clearly separable from each other based on the severity of the damage.

The feature also separates the corroded bearings from the baselines. Though there seems to be a higher overlap between the three corroded specimens. This is expected as the same amount of saltwater has resulted in similar level of corrosion in all the three bearings.



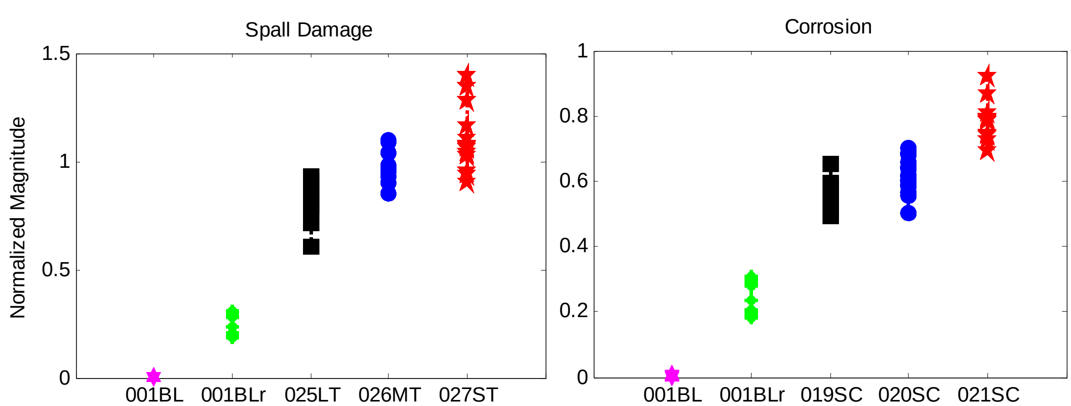
(a) (b)

Figure 2. Intrinsic mode functions IMF1 through IMF4: (a) Healthy (b) Defective bearings.



(a) (b)

Figure 3. Hilbert-Huang Transfroms: (a) Healthy (b) Defective bearings.



(a) (b)

Figure 4. Scatter plots of condition indicative feature: (a) Spalled (b) Corroded bearings.

CONCLUSIONS

This paper presented a diagnostic and prognostic approach for rotorcraft bearing health monitoring using the Hilbert-Huang Transform (HHT). The HHT represents the raw vibration signal in a two-dimensional time-frequency domain by extracting the instantaneous frequency components from the signal using an empirical mode decomposition EMD process. EMD decomposes the complex vibration signal into simple oscillatory modes called intrinsic mode functions (IMF). Since the IMFs are obtained based on the local characteristics time scale of the data, they are applicable for the analysis of nonlinear and nonstationary bearing degradation process.

To perform diagnostics, the authors used the energy ratios of the highest two intrinsic modes and the maximum amplitudes of the respective marginal frequencies as condition indicative features. Although the data set used is small and from component-level test rig, the EMD features have shown to efficiently classify spall and corrosion damages based on severity levels. Accordingly, these features have a potential to reliably diagnose both discrete (spall) and wide spread (corrosion) faults. Work is still in progress to further analyze the reliability of the approach using additional test data.

REFERENCES

1. Hess, A., W. Hardman, H. Chin, and J. Gill, "The US Navy's Helicopter Integrated Diagnostics System (HIDS) Program: Power Drive Train Crack Detection Diagnostics and Prognostics, Life Usage Monitoring, and Damage Tolerance; Techniques, Methodologies, and Experiences," NATO Conference, 1999.
2. Zhang B, G. Georgoulas, M. Orchard, A. Saxena, D. Brown, G. Vachtsevanos, and S. Liang, 2008. "Rolling element bearing feature extraction and anomaly detection based on vibration monitoring," 16th Mediterranean Conference on Control and Automation, Ajaccio, France
3. Randall, R. R, J. Antoni, and F. Bonnardot, 2004. "Recent Advances in Bearing Diagnostic Techniques for Helicopter Gearboxes," Proceedings of the 58th Mechanical Failures Prevention Technology Meeting, Virginia Beach, VA
4. Jacobsen E. and Lyons R. 2003. "The sliding DFT" *Signal Processing Magazine,* 20(2):74–80
5. Lee H, J. Sheldon, M. Watson, and C. Byington. 2011. "Diagnosing Bearing Corrosion using Joint Time Frequency Vibration Analysis," presented at the American Helicopter Society 67th Annual Forum, Virginia Beach, May 3-5, 2011.
6. Yan R., and R Gao. 2006. "Hilbert-Huang Transform-Based Vibration Signal Analysis for Machine Health Monitoring," *IEEE Trans. Instrum. Meas.* 55(6):2320:2329
7. Qiu H., J. Lee, J. Lin, G. Yu. 2005. "Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics," *J. of Sound and Vibration*
8. Lin, J. and L. Qu, 2000. "Feature Extraction Based on Morelt Wavelet and its Application for Mechanical Faul Diagnosis", *J. Sound. Vib.* 234(1):135-148
9. Huang N. E., Z. Shen, and S.R. Long. 1998 "The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis," Proc. Royal. Soc. London, 454: 903–995.
10. Gao R. and R. Yan, 2006 "Nonstationary signal processing for bearing health monitoring," *Int. J. Manuf. Res.*, 1(1):18–40.
11. Dykas B., Krantz T., Decker H., Lewicki D. 2009. "Experimental Determination of AH-64 Apache Tail shaft Hanger Bearing Vibration Characteristics with Seeded Faults," presented at the American Helicopter Society 65th Annual Forum, Grapvine TX, May 27-29, 2009.